International Journal of Electronics, Communication & Instrumentation Engineering Research and Development (IJECIERD)
ISSN(P): 2249-684X; ISSN(E): 2249-7951
Vol. 3, Issue 5, Dec 2013, 39-52

TRANS STELLAR • Journal Publications • Research Consultancy

A TECHNIQUE TO DETECT MASSES FROM DIGITAL MAMMOGRAMS USING ARTIFICIAL NEURAL NETWORK

SAURABH VERMA, KUMAR MANU, MANSI VASHISHT & MONICA KATHURIA

Assistant Professor, ECE Department, M.I.T., Moradabad, Uttar Pradesh, India

ABSTRACT

In this paper we present a technique to detect masses from digital mammograms using Artificial Neural Network (ANN), which performs malignant-normal classification on region of interest (ROI) that contains mass. The major mammographic characteristics for mass classification are Intensity, Shape and Texture. ANN exploits all such type of important factor to classify the mass into malignant or normal. The features used in characterizing the masses are mean, standard deviation, skewness, area, perimeter, homogeneity, energy, contrast and entropy. The main aim of the method is to increase the effectiveness and accuracy of the classification process in an objective manner to reduce the numbers of false-positive of malignancies. ANN with nine features was proposed for classifying the marked regions into malignant and normal. With ANN classifier, experiment result shows the 96.875% accuracy, 96.551% sensitivity and 97.142% specificity.

KEYWORDS: Artificial Neural Network, Digitized Mammograms, Intensity, Shape and Texture Features

INTRODUCTION

The incidence of breast cancer is low in India, but rising. Breast cancer is the commonest cancer of urban Indian women and the second commonest in the rural women. Owing to the lack of awareness to this disease and in absence of a breast cancer screening program. A recent study of breast cancer risk in India revealed that 1 in 28 women develop breast cancer during her life time [1]. This is higher in urban areas being in 1 in 22 in a lifetime compared to the rural areas where this risk is relatively much lower being 1 in 60 women developing breast cancer in their lifetime. In India the average age of the high risk group in India is 43-46 years unlike in the west where women aged 53-57 years are more prone to breast cancer.

A report estimated that one in eight women in the U.S. and one in thirteen in Australia develops breast cancer during their life time. Breast cancer continues to be significant public health problem among women around the world. It has become the number one cause of

Cancer deaths amongst Malaysian women. In the European Community, breast cancer represents 19% of cancer deaths and the 24% of all cancer cases. Nearly 25% of all breast cancer deaths occur in women diagnosed between ages 40 and 49 years.

In order to reduce morbidity and mortality, early detection of breast cancer is essential. However, the appearances of breast cancer are very subtle and unstable in their early stages. Therefore, doctors and radiologists can miss the abnormality easily if they only diagnose by experience. The mammography technology can help doctors and radiologists in getting a more reliable and effective diagnosis. Since it checks mammograms as the “second reader”, thus giving to doctors and radiologist a favorable advice.

Digital mammography is the best available examination for the detection of early signs of breast cancer and it can

reveal pronounced evidence of abnormality such as masses and calcifications. Like a standard mammogram, a digital mammogram uses x-rays to produce an image of the breast. The differences are in the way the image is recorded, viewed by the doctor, and stored. Standard mammograms are recorded on large sheet of photographic film. Digital mammograms are recorded and stored on a computer. After the exam, the doctors can view them on a computer screen and adjust the image size, brightness, or contrast to see certain areas more clearly. Digital images can also be sent electronically to another site for a consultation with breast specialists. While the digital option is not available at all centres, it is becoming more widely available.

In this paper automatic mass classification into malignant and normal is presented based on the statistical and textural features extracted from mass from the breast region using ANN. This paper is organized as follows. Section2 briefly reviews some existing techniques for mass classification followed by artificial neural network (ANN) in section 3. Statistical and texture features are described in section 4.section 5 describes the proposed methods for mass classification. Section 6 demonstrates some simulation results and their performance evaluation, finally conclusion are presented in section 7.

LITERATURE SURVEY

Breast cancer is the most common cancer and continues to be a significant public health problem among women around the world. Medical imaging systems are constantly improving in image quality because of increased image resolution. This results in a growing number of images that have to be inspected for diagnosis. Only the early detection and diagnosis is the way of control but it is a major challenge in India due to lack of awareness and lethargy of Indian women towards the health care and regular check-up. Detection of abnormal masses within breast as well as breast image segmentation is a very important feature in image analysis. Radiologists interpret the mammogram images for detect the abnormalities of cancerous cells such as clustered micro-calcifications (MCCs), masses, architectural distortion ,asymmetry between breasts, breast edema and lymphadenopathy. Then, they will diagnose the abnormalities to determine the status of breast cancer whether it is benign or malignant. In recent years, a few researchers in either academia or industry have used different approaches to do the classification of masses.

Jawed Nagi et.al in [8] developed an automated technique for mammogram segmentation. The proposed algorithm using morphological preprocessing and seeded region growing (SRG) to remove digitization noises, suppress radiopaque artifacts and remove the pectoral muscle to accentuate the breast profile region for use in CAD algorithms.

Jelena Bozek et.al in [9] described a computer-aided detection and diagnosis of breast abnormalities in digital Mammography. Masses calcifications, architectural distortion and bilateral asymmetry are defined with wide range of features and can indicate malignant changes but can also be a part of benign changes. Most of the features such as shape, margin distribution size etc. can be detected by using developed algorithms. However, there are some problems in detection and diagnose of breast abnormalities specific for particular lesion. Some of the problems are visibility of lesion, possibility to differ it from surrounding tissue and appropriate classification of the change as malignant or benign.

Nawazish Naveed *et.al* in [10] has proposed a malignancy and abnormality detection of mammograms using DWT features and ensembling of classifiers. The main complexity about digital mammogram diagnosis is the detection of malignant images and its classification on the basis of abnormalities present. Author investigated the accuracy of detection methodology that uses DWT features as an input to different classifiers like K-nearest neighbor (KNN), Artificial neural networks (ANN) and Support Vector Machine (SVM) and ensemble the results generated by these classifiers. Next, the malignant images are passed through a bank of these ensemble classifiers which are again trained for classification of

different abnormalities. One against all approaches is used for multi-classification. Each ensemble classifier is trained for one abnormality. That particular classifier assigns probability to the abnormality for which it is trained. Median, Mean and product rules are used to combine the result of binary classifiers.

A mass lesion detection using wavelet decomposition transform and support vector machine has been proposed by Ayman Abu Baker et.al in [11]. The proposed method is designed using three main stages, detection region of interest, extraction wavelet features and support vector machine (SVM). In detection region of interest the morphological processing, object labeling, and size filtering are implemented. The main purpose for this technique is to study the properties of true positive (TP) and false positive (FP) detected regions in the mammogram images by analyzing their wavelet features and support vector machine (SVM). The combination of wavelet feature and support vector machine (SVM) has been used to reduce number of the detected FP regions.

Nevine H. Eltonsy et.al in [12] developed a concentric morphology model for the detection of masses in mammography. The technique is based on the presence of concentric layers surrounding a focal area with suspicious morphological characteristics and low relative incidence in the breast region. Mammographic locations with high concentration of concentric layers with progressively lower average intensity are considered suspicious deviations from normal parenchyma. Morphologic concentric layer analysis is a promising strategy for screening mammograms to identify locations highly suspicious to contain malignant masses while maintain the detection rate of benign masses significantly lower.

Byung-Woo Hong et.al in [13] has proposed a segmentation of regions of interest in mammograms topographic approach. A topographic representation has been developed using isolevel contours. The topological and geometrical relationships between contours are analyzed using the inclusion tree. A breast coordinate system can be stabilized after segmentation of the breast boundary and the pectoral muscle. This coordinate system may provide useful information for the identification of masses and registration of two mammograms. A topographic representation is largely invariant to brightness and contrast, and it provides a robust and efficient representation for the characterization of mammographic features.

Shih-Chung B.Lo et.al in [14] has proposed a multiple circular path convolution neural network system for detection of mammographic masses. Multiple circular path convolution neural network architecture specifically designed for the analysis of tumor and tumor-like structure has been constructed. Author first divided each suspected tumor area into sectors and computed the defined mass features for each sector independently. These sector features were used on the input layer and were coordinated by convolution kernels of different sizes that propagated signals to the second layer in the neural network system. The MCPCNN is capable of analyzing correlated features within the sector and between adjacent sectors, which led to an improvement in detecting mammographic masses.

Weidong Xu et.al in [15] described a new ANN-based detection algorithm of the masses in digital mammograms. It firstly built up two mass models to represent the masses with different backgrounds and features, and used different detection methods on different type of masses: for those masses inside the fatty tissue, iterative thresholding was applied to locate them; for those masses in the denser tissue, black hole registration based on discrete wavelet transform (DWT) were used instead. Then, filling dilation was used to extract the whole masses from the background, which was adjusted adaptively by ANFIS.

Pradeep N et.al in [16] described the method for feature extraction of mammograms. Pattern recognition in image processing requires the extraction of features from ROI of the image, the processing of these features with a pattern

recognition algorithm. Features are nothing but observable patterns in the image which gives some information about the image. For every pattern classification problem, the most important stage is feature extraction. The accuracy of the classification depends on the feature extraction stage. The different features that can be extracted for a digital mammogram are: Texture features, Statistical feature, and Structure feature.

Ioan Buciu et.al in [17] has given directional features for automatic tumor classification of mammogram images. Patches around tumors are manually extracted to segment the abnormal areas from the remaining of the image, considered as background. The mammogram images are filtered using Gabor wavelets and directional features are extracted at different orientation and frequencies. Principal Component Analysis is employed to reduce the dimension of filtered and unfiltered high-dimensional data. Support Vector Machine are used to final classify the data. The robustness of Gabor features for digital mammogram images distorted by the Poisson noise with different intensity levels is also addressed.

M. Sundaram et.al in [18] proposed a method of histogram modified local contrast enhancement for mammogram images. In this method, author adjust the level of contrast enhancement, which in turn gives the resultant image a strong contrast and also brings the local details present in the original image for more relevant interpretation. It incorporates a two stage processing both histogram modifications as an optimization technique and a local contrast enhancement technique. The performance of this method is determined using three parameters like Enhancement Measure (EME), Absolute Mean Brightness Error (AMBE) and Discrete Entropy (H) for all 22 numbers of Mias mammogram images with microcalcification. Its enhancement potential is also tested by sobel and otsu methods for the detection of microcalcification in the mammogram image.

ARTIFICIAL NEURAL NETWORK

Artificial Neural Network (ANN) is a powerful classifier that representfs input/output relationships. It resembles human brain in acquiring knowledge through learning and storing knowledge within inter-neuron connection strengths. ANN’s synaptic weights are adjusted or trained so that a particular input lead to specific desired or target output. Figure 1 shows the block diagram for supervised learning ANN, where the network is adjusted based on comparing neural network output to the desired output until the network output matches the desired output. Once the network is trained it can be used to test new input data using the weights provided from the training session.

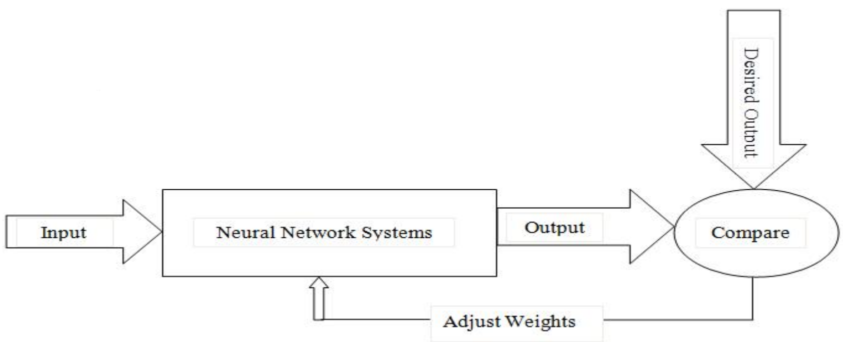


Figure 1: Supervised Learning of ANN

STATISTICAL AND TEXTURE FEATURES

The major mammographic characteristics for mass classification are Intensity, Shape and Texture. Statistical and texture features are extracted for each ROI. The extracted features are then used in neural network classifier to train it for the recognition of a particular ROI of similar nature. These features are mean, standard deviation, skewness, area, perimeter, homogeneity, energy, contrast and entropy. These are adopted from [10, 15, 16].

Mean Value

The mean is also known as average gray level of pixel of pixels in ROI. The mean estimates the value in the image in which central clustering occurs. The mean can be calculated using the formula:

$$\mu = \frac{1}{M\,N}\sum_{i=1}^{M}\sum_{j=1}^{N} p(i,j) \tag{1}$$

Where p(i,j), is the pixel value at point (i,j) of an image of size MxN.

Standard Deviation

The Standard Deviation, σ is the estimate of the mean square deviation of grey pixel value p (i,j) its mean value (μ). Standard deviation describes the dispersion with in a local region. It is determined using the formula:

$$\sigma = \sqrt{\frac{1}{M\,N}\sum_{i=1}^{M}\sum_{j=1}^{N}(p(i,j)-\mu)^2} \tag{2}$$

Skewness

Skewness, S characterizes the degree of asymmetry of pixel distribution in the specified window or ROI around its mean. Skewness is a pure number that characterizes only the shape of distribution. The formula for finding Skewness is given in the below equation:

$$S = \frac{1}{M\,N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(\frac{(p(i,j)-\mu)}{\sigma}\right)^3 \tag{3}$$

Area

This is equal to the sum of all the pixels covered by the ROI. That is, area of the ROI in a digital mammogram image is number of pixels in the ROI. Thus we can compute the area of the ROI by simply given formula below:

$$A = \text{Total number of pixels} \tag{4}$$

Perimeter

The perimeter (P) is equal to the sum of side the side lengths.

$$P = \sum \text{side lenths} \tag{5}$$

Homogeneity

Homogeneity is defined using gray-level co-occurrence matrix as given below:

$$\text{Homogeneity} = \sum_{i,j}\frac{P[i,j]}{1+|i-j|} \tag{6}$$

Energy

Energy is the sum of squared elements in the Gray Level Co-occurrence Matrix (GLCM). Energy is also known as uniformity. The range of energy is [0 1]. Energy is 1for constant image. The formula for finding energy is given below equation:

$$E = \sum_{i,j} P^2(i,j) \tag{7}$$

Contrast

Contrast is a measure of the intensity contrast between a pixel and its neighbor over the whole image. Contrast is calculated by using the equation given below:

$$C = \sum_{i,j} |i-j|^2 P(i,j) \tag{8}$$

Entropy

Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. Entropy, H can also be used to describe the distribution variation in a region. Overall Entropy of the image can be calculated as:

$$H = -\sum_{k=0}^{L-1} Pr_k(\log_2 Pr_k) \tag{9}$$

where, Pr is the probability of the kth grey level, which can be calculated as Zk/m*n, Zk is the total number of pixels with the kth grey level and L is the total number of grey levels.

PROPOSED METHODS

In order to overcome the problems of various existing techniques for sensitivity and accuracy, performance of detection of abnormal masses from mammographic images, the attainment of following objectives are required a method of detection of abnormal masses in digital mammogram to give high accuracy, high sensitivity, low rate of false positive and false negative, increased true positive rate.

As per the above mentioned objectives, to implement a new method for evaluating performance of mammographic images the following steps are to be performed:

- Firstly to obtain the data from Mammographic Image Analysis Society (MIAS) database.
- Apply the image enhancement technique such as histogram equalization on input images.
- Then, segment the image for region of interest (ROI).
- Next, extracting 9 features from ROI such as intensity, shape, and texture features.
- Next, feed the features to feed-forward neural network.
- Finally, classify and decide whether the input mammogram image is malignant or normal image.

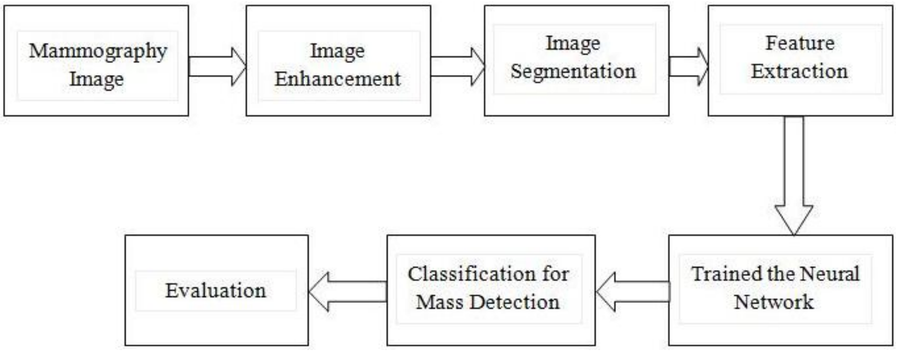


Figure 2: System for Mass Detection

SIMULATION RESULTS AND PERFORMANCE EVALUATION

Image Database

To develop and evaluate the proposed system we used the Mammographic Image Analysis Society (MiniMIAS) [16] database. It is an organization of UK research group. Films were taken from UK National Breast Screening Programme that includes radiologist's "truth" marking on the locations of any abnormalities that may be present. Images are available online at the Pilot European Images Processing Archive (PEIPA) at the University of Essex. This database contains left and right breast images for a total of 161 (322 images) patients with ages between 50 and 65. All images are digitized at a resolution of 1024 x 1024 pixels and at 8-bit gray scale level. The existing data in the collection consists of the location of the abnormality (like the centre of a circle surrounding the tumor), its radius, breast position (left or right), type of breast tissue 9fatty, fatty-glandular and dense) and tumor type if it exists (benign or malign). Each of the abnormalities has been diagnosed and confirmed by a biopsy to indicate its severity. In this database, 42 images contain abnormalities (malignant masses) and 106 images are classed as normal and rest of them either contains microcalcification or benign.

Database for Experiment

In this experiment, Mammography Image Analysis Society (MIAS) database is used with 64 mammograms including 29 malignant mammograms, and 35 normal mammograms.

For classification stage, divide the database into training set and testing set.

Malignant Has 29 Mammograms (15 for Training / 29 for Testing)

G - CIRC: 1 for training/ 1 for testing.

F – CIRC: 1 for training/ 2 for testing.

G – ASYM: 1 for training/ 2 for testing.

D – ASYM: 2 for training/ 2 for testing.

F – ASYM: 0 for training/ 2 for testing.

G – ARCH: 2 for training/ 3 for testing.

F – ARCH: 1 for training/ 2 for testing.

D – ARCH: 2 for training/ 4 for testing.

F – SPIC: 2 for training/ 2 for testing.

G – SPIC: 0 for training/ 3 for testing.

D – SPIC: 0 for training/ 1 for testing.

G – CALC: 1 for training/ 1 for testing.

D – CALC: 1 for training/ 1 for testing.

F – CALC: 0 for training/ 1 for testing.

F – MISC: 1 for training/ 1 for testing.

D – MISC: 0 for training/ 1 for testing.

Normal Has 35 Mammograms (17 for Training/ 35 for Testing)

F – NORM: 17 for training/ 27 for testing.

D – NORM: 0 for training/ 4 for testing.

G – NORM: 0 for training/ 4 for testing.

Results and Performance

Input images are taken from Mammography Image Analysis Society (MIAS) database. These images have some noises. Before processing of these images, noises are removed. So image enhancement technique, used histogram equalization method for enhancing the images. After then, segmentation technique is required for extracting the region of interest (ROI) from the mammogram images. Next, extraction of the features such as area, average gray level (mean), standard deviation, skewness, perimeter, homogeneity, energy, contrast and entropy from the selected ROI of the mammogram image is required. Next, trained the feed-forward neural network with the help of these above mentioned extracted features. This neural network has one input, two hidden layer, and one output. For mass classification neural network target is set to 1 or 0 value. In this design methodology, consider the malignant or normal case of breast cancer. For mass classification, neural network's output give the value 1 or malignant mass and value 0 for normal mass.

Histogram Equalization

The histogram of a digital image with gray levels in the range [0, L−1] is a discrete function

$g(r_k) = n_k$, where r_k is the kth gray level and n_k is the number of pixels in the image having gray level r_k.

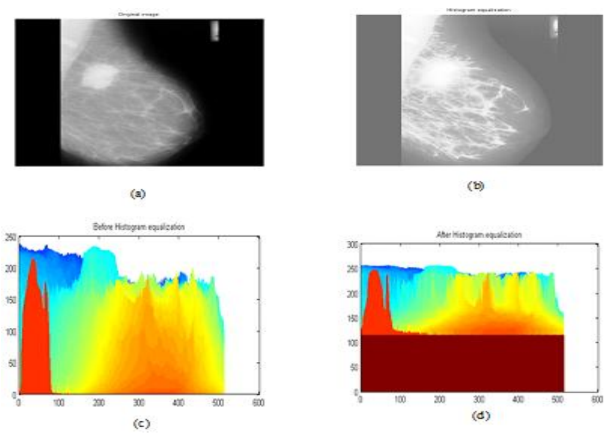


Figure 3: Malignant (mdb 184.pgm) MIAS Database (a) Original Mammogram Image; (b) Histogram Equalization Image (Enhanced Image); (c) before Histogram Equalization Distribution Plot. (d) After Histogram Equalization Distribution Plot

Table 1: Cumulative Histogram Distribution for Malignant (mdb184) Case

Bin	Histogram	Probability	Cumulative histogram	CDF	Output
1	118490	0.4520	118490	0.4520	115
2	4932	0.0188	123422	0.4708	120
3	2946	0.0112	126368	0.4821	123
4	2822	0.0108	129190	0.4928	126
5	1742	0.0066	130932	0.4995	127
6	1122	0.0043	132054	0.5037	128
7	1088	0.0042	133142	0.5079	130
8	923	0.0035	134065	0.5114	130
9	751	0.0029	134816	0.5143	131
10	735	0.0028	135551	0.5171	132
11	690	0.0026	136241	0.5197	133
12	589	0.0022	136830	0.5220	133
13	585	0.0022	137415	0.5242	134
14	525	0.0020	137940	0.5262	134
15	542	0.0021	138482	0.5283	135
16	520	0.0020	139002	0.5303	135
17	441	0.0017	139443	0.5319	136
18	426	0.0016	139869	0.5336	136
19	376	0.0014	140245	0.5350	136
20	365	0.0014	140610	0.5364	137
21	389	0.0015	140999	0.5379	137
22	362	0.0014	141361	0.5392	138
23	353	0.0013	141714	0.5406	138
24	348	0.0013	142062	0.5419	138
25	338	0.0013	142400	0.5432	139
26	364	0.0014	142764	0.5446	139
27	335	0.0013	143099	0.5459	139
28	340	0.0013	143439	0.5472	140
29	326	0.0012	143765	0.5484	140
30	331	0.0013	144096	0.5497	140
31	308	0.0012	144404	0.5509	140
32	301	0.0011	144705	0.5520	141
33	300	0.0011	145005	0.5532	141

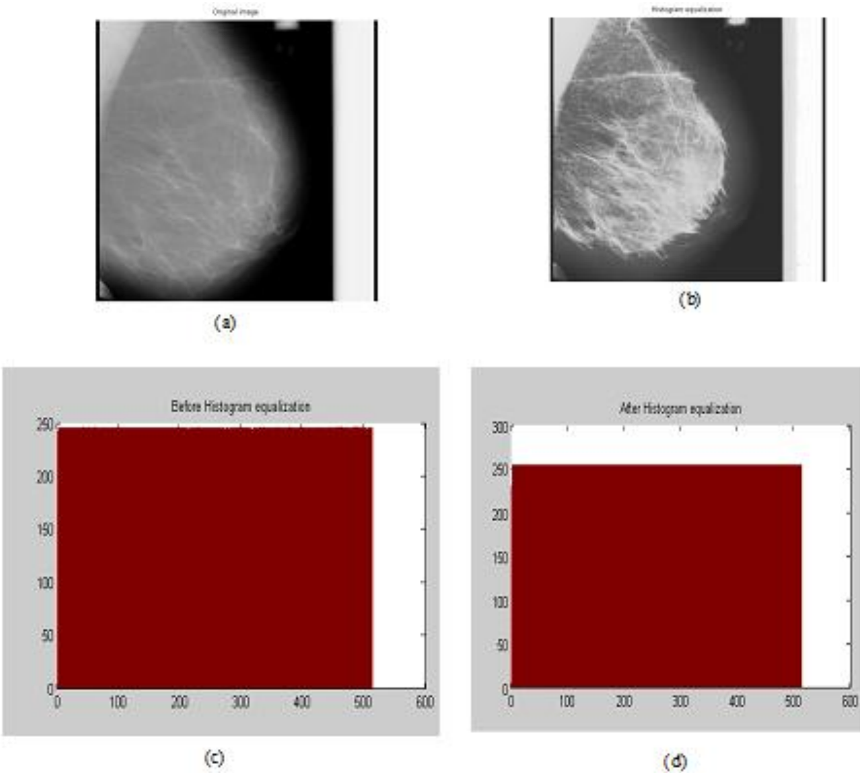
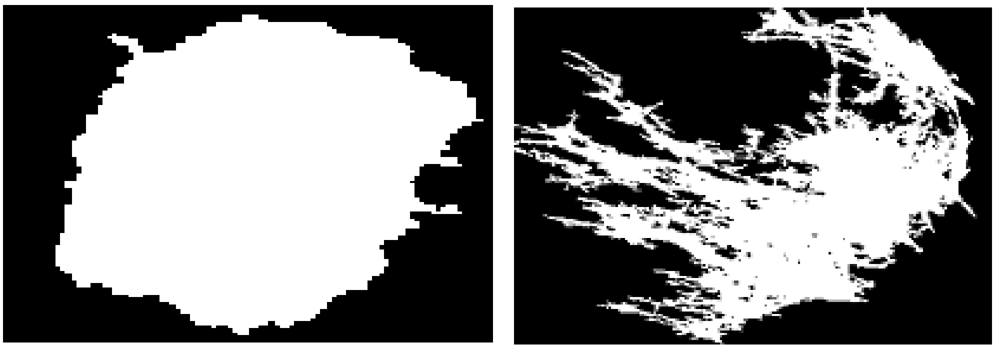


Figure 4: Normal (mdb 140.pgm) MIAS Database (a) Original Image; (b) Histogram Equalization Image (Enhanced Image); (c) before Histogram Equalization Distribution Plot. (d) after Histogram Equalization Distribution Plot

Table 2: Cumulative Histogram Distribution for Normal (mdb140) Case

Bin	Histogram	Probability	Cumulative histogram	CDF	Output
1	44337	0.1691	44337	0.1691	43
2	865	0.0033	45202	0.1724	44
3	1024	0.0039	46226	0.1763	45
4	1096	0.0042	47322	0.1805	46
5	983	0.0037	48305	0.1843	47
6	1079	0.0041	49384	0.1884	48
7	937	0.0036	50321	0.1920	49
8	824	0.0031	51145	0.1951	50
9	759	0.0029	51904	0.1980	50
10	665	0.0025	52569	0.2005	51
11	656	0.0025	53225	0.2030	52
12	680	0.0026	53905	0.2056	52
13	648	0.0025	54553	0.2081	53
14	687	0.0026	55240	0.2107	54
15	658	0.0025	55898	0.2132	54
16	570	0.0022	56468	0.2154	55
17	1075	0.0041	57543	0.2195	56
18	548	0.0021	58091	0.2216	57
19	560	0.0021	58651	0.2237	57
20	561	0.0021	59212	0.2259	58
21	562	0.0021	59774	0.2280	58
22	519	0.0020	60293	0.2300	59
23	484	0.0018	60777	0.2318	59
24	515	0.0020	61292	0.2338	60
25	504	0.0019	61796	0.2357	60
26	467	0.0018	62263	0.2375	61
27	443	0.0017	62706	0.2392	61
28	441	0.0017	63147	0.2409	61
29	441	0.0017	63588	0.2426	62
30	392	0.0015	63980	0.2441	62
31	388	0.0015	64368	0.2455	63
32	352	0.0013	64720	0.2469	63
33	364	0.0014	65084	0.2483	63

Segmentation of Enhancement Images



(a) mdb 184 (b) mdb 140

Figure 5: (a) Segmented Result (ROI) of Malignant Mammogram; (b) Segmented Result (ROI) of Normal Mammogram

Result of Mass Detection

Nine parameters i.e. area, mean, standard deviation, skewness, perimeter, homogeneity, contrast, energy and entropy are taken for trained the ANN. Finally, result of mass detection from digital mammogram, have the table of all mammograms as follow:

Table 3: Output Result of ANN

	Total Number	Correct	False
Malignant	29	28	1
Normal	35	34	1

TP: Predicts malignant as malignant. TN: Predicts normal as normal.

FN: Predicts malignant as normal. FP: Predicts normal as malignant.

Performance Evaluation

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} = \frac{28 + 34}{28 + 34 + 1 + 1} = \frac{62}{64} = 96.875\ \%$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} = \frac{28}{28 + 1} = \frac{28}{29} = 96.551\ \%$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} = \frac{34}{34 + 1} = \frac{34}{35} = 97.142\ \%$$

$$\text{Error} = \frac{\text{FP} + \text{FN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} = \frac{1 + 1}{28 + 34 + 1 + 1} = \frac{2}{64} = 3.125\ \%$$

Simulation Results

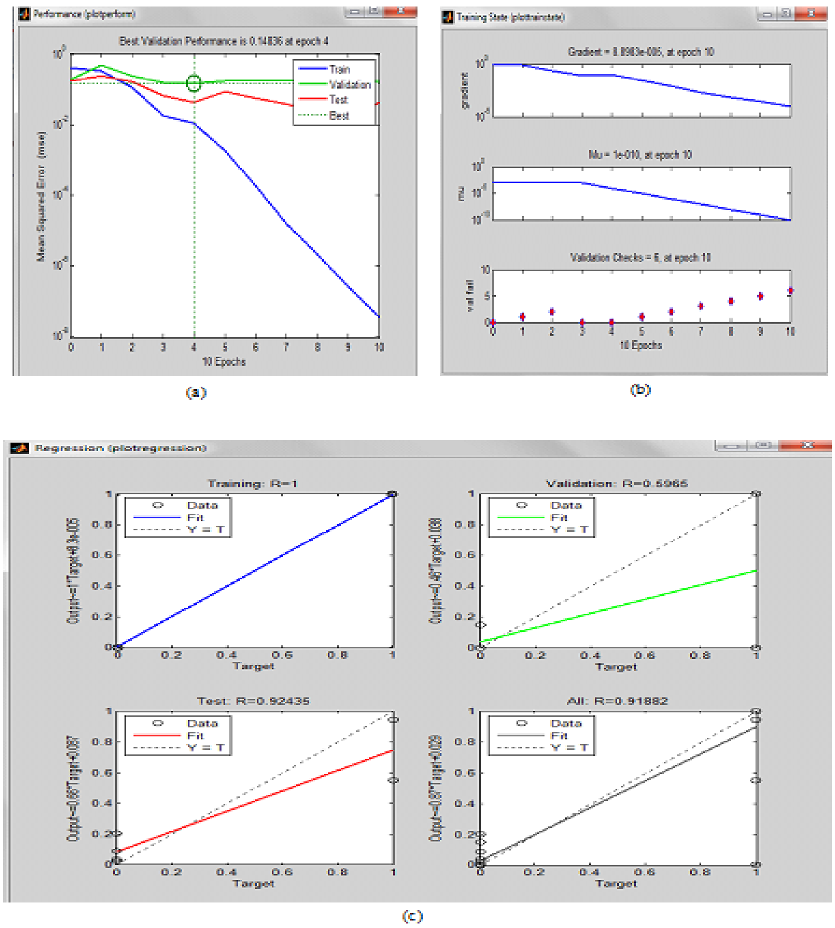


Figure 6: Simulation Results: (a) Performance Plot; (b) Training State Plot; (c) Regression Plot

CONCLUSIONS

Mass classification is a vital stage for the performance of the computer aided breast cancer detection. Different classifiers were used in biomedical imaging application like breast cancer detection from mammogram. However, ANN shows very good performance in medical diagnostic systems. In this paper, before processing, the enhancement image has been taken from histogram equalization technique. Then, segmentation technique is used to

extract the region of interest (ROI). ROI is extracted using peak analysis from the histogram of the breast tissue. Therefore, also get the exact boundaries of suspicious regions, and it is now convenient to obtain good shape feature for classification. In this paper, the proposed features are good descriptions especially for speculated masses. With artificial neural network (ANN) classifier, experiment result shows that the accuracy of this method is good i.e. 96.875%, because it have low false positive and false negative rate. Furthermore, the True Positive detection rate of this methodology is good for a data set 64 mammograms. Moreover, proposed this method is simple and it takes less time for iterations. Therefore, it is effective in terms of time consuming and precision.

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